

Remaining Useful Life Prediction of Rolling Element Bearings Based On Health State Assessment

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ABSTRACT

Remaining useful life (RUL) prediction is one of key technologies to realize prognostics and health management that is being widely applied in many industrial systems to ensure high system availability over their life cycles. The present work proposes a data-driven method of RUL prediction based on multiple health state assessment for rolling element bearings. Instead of finding a unique RUL prediction model, the life cycle of bearings is clustered into three health states: the normal state, the degradation state, and the failure state. A local RUL prediction model is separately built in each health state. Support vector machine is the technology to implement both health state assessment (classification) and RUL prediction modeling (regression). Experimental results on two accelerated life tests of rolling element bearings demonstrate the effectiveness of the proposed method.

1. INTRODUCTION

Bearings are the most common components in rotatory machines, and their failures are the most common failure cases in machinery. With increasing requirement of reliability, maintainability, testability, supportability and safety, extensive principles and models on the topic of bearing failure physics, diagnosis and prognostics have been reported in literature every year; however, most prognostic models do not have accuracy long-term prediction for the purpose of industrial applications, and thus prognostics techniques for remaining useful life (RUL) prediction are still quite challenging in both academia and industries (Kim et al. 2012, Siegel et al. 2011, Sun et al. 2011, Wang 2012).

Ideally, RUL prediction can be viewed as a regression problem where a connection model between the sensitive features and the corresponding RUL is built over the complete life time. However, the methods using a unique regression model may be hard to represent the entire history and easily over fit the inconsistent patterns in some features (Wang 2012), because the trend of vibration based features is not necessarily monotonic with respect to degradation of bearings. In recent years, there is a trend that RUL prediction is suggested to be achieved individually on different health states (Kim et al. 2012). It implies the difference of intrinsic characteristics within different health states. Wang (Wang 2012) proposed two RUL prediction strategies to address the scenarios when the bearing faults have and have not been detected. Sutrisno et al (Sutrisno et al. 2012) realized degradation state recognition of bearings and estimated RUL based on making comparisons on durations of degradation states between the training and test bearings. Medjaher et al (Medjaher et al. 2012) proposed a data-driven method using mixture of Gaussian hidden Markova model (represented by dynamic Bayesian networks) to represent health states of bearings. Zhu et al (Zhu et al. 2013) proposed a performance degradation assessment method based on rough support vector data description. Siegel et al (Siegel et al. 2011) proposed a general methodology of how to perform rolling element bearing prognostics and presented the results using a robust regression curve fitting approach.

In the present work, we propose a RUL prediction method based on multiple health state assessment. Instead of looking for an overall regression model, we divide the entire bearing life into several health states where a local regression model can be trained separately. With the history life data from training bearings, we extract the characteristic features and knowledge about labels of health state, and then a classification model is built for health state assessment. We adopt SVM as the technique to implement

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both health state assessment (classification) and local RUL prediction (regression), as SVM has been proved to be a suitable tool for both classification and regression problems.

2. PROPOSED METHOD

The proposed method includes two phases: training phase and testing phase. See Figure 1. The training phase generates a health state assessment model and local RUL prediction models corresponding to each health state. The testing phase uses the generated models from the training phase to estimate RUL when a new online sample is available.

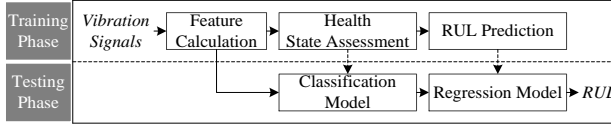


Figure 1. Flow chart of the proposed method

2.1 Health State Assessment

Health state assessment divides the whole life circle of bearings into several degradation states where RUL prediction model can be trained separately. In other words, the health state of a time point is recognized at first, and then the method adaptively selects the corresponding model to predict its RUL. The way of using health state assessment is the key idea of the proposed method, as we believe that RUL prediction models are not necessary the same in different health states. Instead of making great efforts to find a uniquely complex model for the whole life time, the piecewise approach based on health state assessment may be more practical.

In this section, we propose a hybrid approach that uses both unsupervised and supervised learning technologies to build a model for health state assessment. As no knowledge about health states is available at the very beginning of the data-driven method, we need to find a rough degradation states to supervise an accurate health state assessment. The idea is illustrated in Figure 2. We first use the unsupervised learning to extract knowledge about health state labels of all the time points. With the provided label knowledge, the supervised learning is employed to build a robust model of health state recognition.

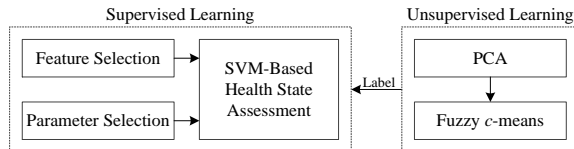


Figure 2. Hybrid approach for health state assessment

From the viewpoint of health state assessment, the run-to-failure data have their own intrinsic characteristics in different states. Therefore, we can use a clustering method to roughly group the run-to-failure data into L clusters,

where L is the predefined number of health states and needs to be specified by users. Fuzzy c -means (Bezdek 1981), a classical method of clustering, is the suggested method of unsupervised learning in the proposed method.

Prior to fuzzy c -means, an unsupervised dimension reduction method is used to extract n' features from the original n features. In this method, principal component analysis (Shlens 2010), a well-known unsupervised technology of dimension reduction, is suggested to remove noisy features and reduce feature dimension while maintaining most of the variability from the original features (98 percentage of variability is used in this paper). By using the unsupervised learning, we can divide the bearing life into L health states by $(L-1)$ obtained thresholds, i.e. t^1, t^2, \dots, t^{L-1} , as shown in Figure 3.

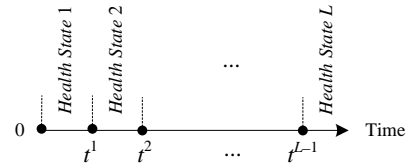


Figure 3. The proposed RUL prediction process

The proposed unsupervised approach can fuse many degradation features, and thus it usually provides a better performance than the approaches based on a single feature. In this paper, we specify the number of clusters to be three. The three health states, including normal state, degradation state, and failure state, are used to describe the bearing life duration. According to the time thresholds from unsupervised learning, we label the samples as one to represent the normal state if $t_i < t^1$, two to represent the degradation state if $t^1 \leq t_i \leq t^2$, and three to represent the failure state if $t_i > t^2$.

Then, the health state assessment becomes a supervised classification problem. In this paper, we use SVM as the classifier to build the model of health state assessment. Feature selection that aims to select an optimal set of features for SVM input can be implemented immediately after time record labeling. Parameter selection is also necessary to select the optimal parameters of SVM. Finally, the decision function of health state assessment is shown as follows:

$$\hat{STA} = \text{sign} \left(\sum_{i=1}^p [\alpha_i y_i \kappa(\mathbf{x}_i, \mathbf{x})] + \frac{1}{p} \sum_{i=1}^p [y_i - \alpha_i y_i \kappa(\mathbf{x}_i, \mathbf{x}_i)] \right), \quad (1)$$

where $\text{sign}()$ is the sign function that extracts the positive or negative sign of a real number; κ is the kernel function; y is the label; α is the Lagrange multiplier; p is the number of support vectors. If $L \geq 3$, the health state assessment is a multiple class classification problem; therefore, the so-

called “one-against-all” approach (Vapnik 1995) is applied to the binary SVM in Eq. (1).

2.2 RUL Prediction

Based on the results from health state assessment, we train individual RUL prediction models on the degradation state and the failure state except the normal state. That is, we do not build the RUL prediction model for the normal state, as the normal state is quite diverse due to the different working condition. The RUL prediction is triggered only if the rolling bearings leave the normal state. By using the historical run-to-failure data, we can build RUL prediction models for the degradation state and the failure state. The technology to implement RUL prediction modeling is support vector machine that has also been used in (Sutrisno et al. 2012). Therefore, the RUL prediction value is computed as follows:

$$\hat{RUL} = \sum_{i=1}^p (\alpha_i - \alpha_i^*) \kappa(\mathbf{x}, \mathbf{x}_i) + \frac{1}{p} \sum_{i=1}^p [y_i - (\alpha_i - \alpha_i^*) \kappa(\mathbf{x}, \mathbf{x}_i) - \varepsilon], \quad (2)$$

where α and α^* is the Lagrange multiplier, ε is the margin of tolerance.

3. APPLICATIONS AND DISCUSSIONS

The proposed method is hereafter applied to experimental data that were collected from accelerated life tests (ALTs) of rolling element bearings. Those data have been used in the IEEE 2012 prognostic and health management (PHM) data challenge competition (Nectoux et al. 2012). The goal of the competition was to provide the best estimated RUL of rolling element bearings. One more thing to do before the following procedures is to clarify the failure criterion as it has great influence on the detailed modeling (Wang 2012). In the challenge, a bearing failure is deemed have happened if the amplitude of the vertical vibration signal exceeds a threshold of 20g (Nectoux et al. 2012).

Feature calculation is the following process after the signal preprocessing. As the failure criterion is vibration amplitude oriented, we define two related features that may reflect the degradation trend of rolling element bearings. The first one is the maximum absolute amplitude among the two vibration sensors. Taking the history vibration data into account, we define the second feature (called vibration-to-history index) as follows:

$$VH_i = \begin{cases} f_i, & \text{if } i = 1 \\ \frac{f_i}{\frac{1}{i-1} \sum_{j=1}^{i-1} f_j}, & \text{if } i > 1 \end{cases} \quad (2)$$

where f_i calculates the maximum absolute amplitude among the two sensors (the first defined feature); VH_i is the value of the vibration-to-history index on the i th time record.

Table 1 summarizes another 33 features adopted in this paper. Together with the specific two features, a total of 68 ($33 \times 2 + 2$) feature values are extracted from the two vibration

accelerometers. We then take the natural logarithm on all the 68 features to obtain possible linear trends, and another 68 new features are generated. Therefore, the total number of features used for the following process is 136. All the features are numbered from 1 to 136 sequentially. The first 66 features follow the same sequence in Table 1. The former half is from the horizontal accelerometer, and the latter half is from the vertical accelerometer. The 67th and 68th features are the two defined features, respectively. The last 68 features are organized the same as the first 68 features. The feature preprocessing including smoothing and normalization is conducted to continue process all the features. We use 11 as the fixed subset size in smoothing. Up to now, the features are ready for the use of both health state assessment and RUL prediction.

Table 1. Feature summary

Domain (#)	Feature
Time-domain (23)	<ul style="list-style-type: none"> • Fourteen conventional statistical features (Liu et al. 2013): maximum absolute value, average absolute value, peak to peak, root mean square (RMS), standard deviation, Skewness, kurtosis, variance, shape factor, crest factor, clearance factor, impulse factor, energy operator, and time series entropy; • Nine empirical mode decomposition (EMD) features (Dong 2012): RMS of the nine IMFs from EMD.
Frequency-domain (10)	<ul style="list-style-type: none"> • Six conventional statistical features (Liu et al. 2013): mean frequency, frequency center, rms frequency, standard deviation frequency, FFT entropy, and Hilbert entropy; • Four fault characterized frequency (Randall & Antoni 2011): ball pass frequency (outer race), ball pass frequency (inner race), fundamental train frequency (cage speed), and ball spin frequency.

In this application, the number of states is set to three. This choice is motivated by the fact that the degradation of the bearings can be represented by three health states: the normal state, the degradation state, and the failure state. With the extracted label knowledge, health state assessment turns to be a supervised classification problem, which is solved by support vector machine. It is worth pointing out that the unsupervised learning is for only the training phase, while the supervised learning is for both the training phase and the test phase. By the suggested feature selection algorithm (Liu et al. 2013), 11 features (i.e. the 71th, 79th, 44th, 69th, 73th, 11th, 72th, 112th, 91th, 24th, and 76th features) are selected for the SVM based health state assessment; 14 features (i.e. the 76th, 79th, 72th, 11th, 70th, 24th, 73th, 92th, 71th, 44th, 82th, 69th, 112th, and 86th features) are selected for the RUL prediction of the degradation state; and 4 features (i.e. the 126th, 90th, 58th, and 74th features) are selected for the RUL prediction

modeling of the failure state. In addition, parameters of SVM are all optimized by an analytical method (Liu et al. 2014) and grid search. We use two historical data, i.e. the bearing1_1 and the bearing1_2, to train the proposed method. This follows the same training and testing ways described in the IEEE 2012 PHM data challenge competition. In the next, we take the bearing1_3 as an example to introduce the rest process of the proposed method. Figure 4 shows the results of health state assessment for the bearing1_3. From Figure 4, the SVM based method of health state assessment performs well except the regions where a health state nearly changes. This phenomenon is caused by the randomness of the model in the transition regions between two health states. Farther away from the transition regions, the randomness becomes much less effective, and the model of health state assessment can work in a stable way.

Figure 5 shows the RUL prediction results by applying the proposed method to the dataset of the bearing1_3. In our strategy, no RUL prediction is made when the health state is estimated as the normal state. This explains that no values in a range from 0 second to about 11350 seconds are plotted in Figure 5. From Figure 5, RUL prediction in the range from 11350 seconds to 17320 seconds is not very match to the true RUL values. This could be possible, as the learning set was quite small while the life duration of all bearings was very wide (from 1 to 7 hours). Performing good estimates was thereby difficult and challenging. The efficacy of data-driven methods is highly dependent on the quantity and quality of system operational data (Kim et al. 2012). A significant amount of past knowledge of the assessed bearing is required because the corresponding failure modes must be known in advance and well-described in order to assess the current health state. However, there is only two bearing datasets for training in the challenge. Performance of the proposed method could be improved if more bearing training datasets are included.

In the next, we compare the proposed method with one reported methods following the same way defined in the challenge. No matter which technologies embraced in a method, the final objective to accurately predict RUL is the same pursue of all the methods. The challenge provides three measures to evaluate RUL prediction results from all the RUL prediction methods. Tables 2 summarize all the results of the two methods for RUL prediction. From the table, we can see that the proposed method performs better than Wang et al (Wang 2012) for the bearing1_3 while performs comparable for the bearing1_4.

Table 2. RUL prediction results

ID	Current Life (s)	True RUL (s)	Wang (Wang 2012)	The Proposed Method
Bearing1_3	18010	5730	490	5842
Bearing1_4	11380	339	10	1109

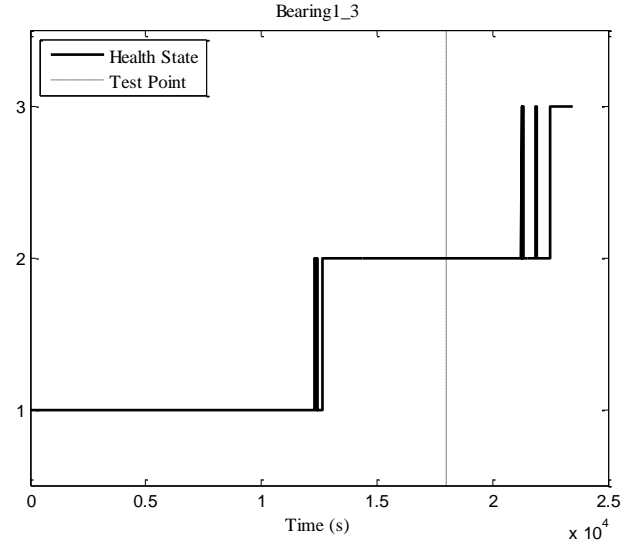


Figure 4. Health state assessment for the bearing1_3

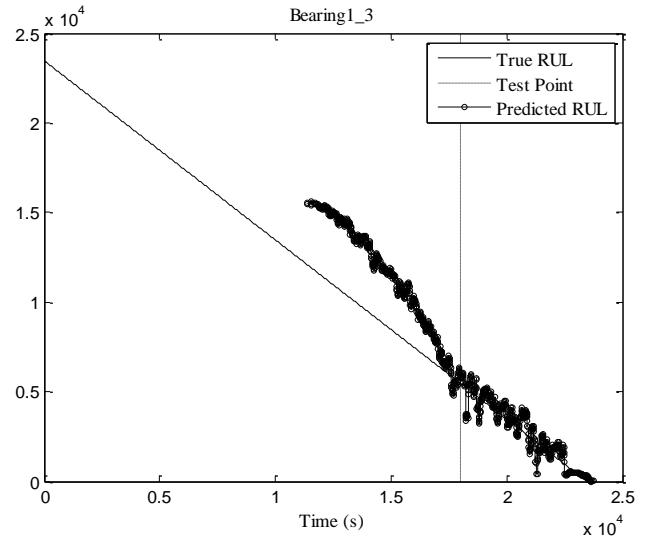


Figure 5. RUL prediction for the bearing1_3

4. CONCLUSIONS

In RUL prediction of bearings, the methods using a unique regression model may be hard to represent the entire history and easily over fit the inconsistent patterns in some features. Therefore, instead of looking for an overall regression model, this paper proposes a RUL prediction method based on multiple health state assessment. It basically includes four process steps: raw data collection, feature calculation, health state assessment, and RUL prediction modeling. With the help of health state assessment, the proposed method divides the entire bearing life into L health states where a local regression model can be built individually. As no knowledge about health states is available at the very beginning of the proposed data-driven method, we propose a

hybrid approach consisting of both unsupervised learning and supervised learning to estimate the health state of a bearing. The unsupervised learning with PCA and fuzzy *c*-means is used to automatically extract knowledge about health state labels of all the time points in the training phase. With the provided label knowledge, the supervised learning is employed to build a health state assessment model. SVM is the technology to implement both the supervised learning of health state assessment and RUL prediction modeling. Experimental results show the effectiveness of the proposed method.

ACKNOWLEDGEMENT

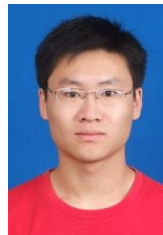
This work was supported by National Natural Science Foundation of China (Grant No. 51375078), and supported by the State Key Laboratory of Rail Traffic Control and Safety (Contract No. RCS2014K006), Beijing Jiaotong University.

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